A Semantic Decision Support System to optimize the energy use of public buildings

A Semantic Decision Support System to optimize the energy use of public buildings

Álvaro Sicilia, asicilia@salleurl.edu
ARC Engineering and Architecture La Salle – Ramon Llull University, Barcelona, Spain

Gonçal Costa, gcosta@salleurl.edu
ARC Engineering and Architecture La Salle – Ramon Llull University, Barcelona, Spain

Vincenzo Corrado, vincenzo.corrado@polito.it
Department of Energy, Politecnico di Torino, Torino, Italy

Alice Gorrino, alice.gorrino@polito.it
Department of Energy, Politecnico di Torino, Torino, Italy

Fulvio Corno, fulvio.corno@polito.it
Department of Control and Computer Engineering, Politecnico di Torino, Torino, Italy

Abstract
Cities are expected to play a key role in the implementation of Europe 2020 strategy, leading to relevant actions towards energy-efficient neighbourhoods. Although there are plenty of energy data and other related data sets available at the city level, their appropriate integration to support decision making processes for local authorities, still remains a challenge. To fill this gap, a web-based Decision Support System (DSS) has been developed within the framework of the OPTIMUS project to support the decision making process, improving the energy efficiency of buildings, by optimizing the energy use in their premises, and reducing CO_2 emissions. In this paper, we presents the semantic framework that has been developed to provide the required interoperability, between the DSS and the different data sources, using Semantic Web technologies. In this framework, the OPTIMUS ontology has been designed to capture and model the information from these data sources. Experimental results derived from the adoption of the ontology are discussed in this paper.

Keywords: DSS, semantic framework, ontology, building energy performance

1 Introduction
Cities are expected to play a key role in the implementation of Europe 2020 strategy. The city authorities need to lead relevant actions towards energy-efficient neighbourhoods. Although there are plenty of energy and other related data sets available at the city level, their appropriate integration to support strategic decisions still remains a challenge. The difficulties of using energy and energy-related data are numerous and diverse. This kind of data can be found in different places and forms with different granularities. The information required for decision making processes in cities, is heterogeneous since it is generated by different systems in various domains. The Open Data movement aims at increasing the quantity of the data, shared by institutions and authorities. Moreover, the linked open data (LOD) initiative promotes opening data sources using Semantic Web technologies. In the context of smart cities, all of these issues requires of a holistic interoperability solution to overcome the intrinsic heterogeneity of real-time data sources.

The purpose of the OPTIMUS project is to develop and implement a web-based decision support system (DSS) to support city authorities (i.e., city executives or city energy managers) in producing short-term energy plans (e.g., 1-week plans), using open data in real-time. One of the technological outputs of the project is a semantic framework which enables cities to share and integrate their data from different domains, –in particular data like: weather conditions, social networks, building energy management systems, energy prices, renewable energy production– using Semantic Web technologies.

This paper presents the design of a semantic framework based on a global ontology created to provide a common layer for interoperability –between the OPTIMUS DSS and the data source–, and to facilitate the DSS operations that involve the processing of energy data and predictive models.

This paper is structured as follows: parts below of this section, briefly introduce the basic concepts around the decision support systems (classification, scenarios and technologies). A discussion is exposed about the possible benefits of the use of semantic web technologies and ontologies for data integration and for ensuring the required interoperability between the decision support systems and the possible data sources used by them. A review of the state of the art on its application in the area of energy efficiency and building performance is provided. Section 2 reviews the background and the possible methodologies that can be applied for a semantic data integration process. Section 3 is dedicated to the description of the semantic framework and the design criteria and process, followed to create the global ontology (structure and coding). Finally, Section 4 presents the process done to integrate the data from different sources into the OPTIMUS DSS for predicting the building behaviour.

1.1 Decision support systems overview

Although, its definition varies depending on the author's point of view (Keen & Scott-Morton 1978, Sprague 1980, and others), a Decision Support System (DSS) can be described as a tool addressed at supporting users and organizations in the decision-making processes. The concept of DSS began to emerge in the 1960s after studying different methods for the use of computerized quantitative models to support these activities. Currently, DSSs are information systems which include knowledge-based systems to help in making decisions in different domains. Here, the term of "knowledge-based systems" refers to systems that use tools, such as ontologies and rules, to represent the explicit knowledge of a knowledge base containing complex structured and unstructured information.

The DSSs can be classified into different types. For example, Daniel J. Power et al. (2002) divide them into: *Communication-driven DSSs* which use a set of parameters provided by decision makers to assist them in analysing its particular problem, *Data-driven DSSs* based on analysing time-series data as well as external and real-time data, *Document-driven DSSs* focused on providing search functionalities to help managers to find documents, *Knowledge-driven DSS*s based on the knowledge extraction from a particular domain to be analysed using data mining methods, and *Model-driven DSSs* which operate on a model of reality rather than on data intensive model such as simulation energy model of a building.

On the other hand, a DSS can be classified according to its purpose such as intelligent decisions, knowledge management, and negotiation support among others (Arnott & Pervan 2005). *Intelligent DSS* are those systems whose purpose is to apply machine learning techniques for data analysis. Many of them include the use of rule-based expert systems as well as neural networks, genetic algorithms and fuzzy logic (Turban et al 2005).

1.2 Use of Semantic Web Technologies for decision support

In recent years, semantic web technologies and ontologies have been applied in the DSS development (Christopher et al 2006, Ding et al 2015).

According to Eva Blomqvist (2012), semantic web technologies can be applied in DSS developments using ontologies and rules as a means to provide intelligent support to decision-making. These semantic technologies can be used, mainly, to support data integration processes, and to overcome the interoperability barriers through standardized formats. In the first case, ontologies can be used to integrate data from different existing sources, sometimes required using real-time data. Here, semantic Web languages like RDF and OWL can be used to provide integrated schema descriptions and a unified view of data. Approaches based on Data integration using these technologies have been studied and implemented by many authors during last years (Calvanese et al 1998; Nemirovski et al 2013; Costa & Madrazo 2014). Other approaches focus on the semantic interoperability concept for providing an explicit semantics and a shared understanding of the data to facilitate the communication among the multiple and heterogeneous data sources (Sicilia et al 2014).

1.3 Decision support systems in energy efficiency

At present, analysis techniques of energy efficiency of buildings used for decision support are limited to a very few data sources. The most commonly used data sources are those provided by a building management system (e.g., energy consumption, temperature, humidity and CO_2), while other such as weather forecasting, social media and occupancy in most cases are not considered (Corry et al 2013).

However, and as a result of the increasing demand to satisfy the current legislative framework; for example, to meet the European directives in terms of energy efficiency in buildings; new paradigms and systems are emerging with the aim of achieving a more comprehensive view of the energy performance of the building. For meeting these requirements, different research projects aimed at integrating multiple data sources for providing new business models and also services have been developed in recent years. This is the case of for example the projects of EEPOS[1] (2015) and EnRiMa[2] (2013).

With a more comprehensive vision of the building information, it is more feasible to address the management and maintenance of a building when multiple domains are involved. Under this vision, some research projects have been focusing on the use of semantic web technologies in order provide generic solutions to particular problems in this area. Some examples of these research projects are SEMANCO[3] (2013), SEMERGY[4] (2014), and KnoholEM[5] (2014):

- SEMANCO platform. Composed of a set of tools for visualization and analysis of energy data of a city. The platform combines interactive 3D models, tables and diagrams to display energy related data. The analysis tools use data mining techniques to enable consultants, policy makers and planners to calculate energy performance indicators. The system developed uses a formal ontology (an energy model) comprising concepts captured from diverse sources including standards, use cases and activity descriptions and data sources related to the domains of urban planning and energy management.
- SEMERGY. According to Ulrich et al., SEMERGY provides a web-based decision support and an optimization environment by incorporating different calculation and simulation methods for the evaluation of the energy, the environmental, and the financial performance of buildings. A semantic interface is provided in this environment to enabling access to semantic data ontologies. The aim is to facilitate the use of the scattered web-based resources such as building products and materials, codes and regulations among others.
- KnoholEM. Project focused on knowledge-based energy management for public buildings through holistic information modelling and 3D visualization. The elaboration of an intelligent energy management solution for energy efficient buildings and spaces for public use was carried out in this project.

The DSS developed in the OPTIMUS project relies on the interconnection of five heterogeneous real-time data sources (i.e., weather conditions, social, building energy management systems, energy prices, renewable energy production) to suggest short-term actions plans to the public authorities with the goal of reducing energy consumption in public buildings. The OPTIMUS approach can be included within the *Data-driven DSS* category. The main differences with the existing DSSs for energy efficiency are the use of different data categories and the use of inverse models –black and grey box– for predicting building behaviour reducing the burden of collecting information of the building.

2 OPTIMUS DSS architecture

The main objective of the DSS is to give suggestions to the public authority in order to better manage the building stock within approximately a week time. Users can perform different actions which are classified in the following fields:

1) Management of the building technical systems (HVAC, lighting…) which includes for example the scheduling of the set point temperature based on the adaptive comfort criteria, the scheduling of

[1] http://www.eepos.co.uk/
[2] http://www.enrima-project.eu/
[3] http://www.semanco-project.eu
[4] http://publik.tuwien.ac.at/files/PubDat_237404.pdf
[5] http://www.knoholem.eu

the optimal start/stop times of the heating/cooling system taking account the time constant of the structure, and the optimization of the operation time of an air-side economizer.

2) Management of the building occupancy which encompasses actions mainly focused on rationalization of the number of conditioned spaces.

3) Planning of the Renewable Energy Sources exploitation which comprises actions focused on the energy produced by renewable sources consumption or selling according to energy prices and weather forecasting.

Each action refers to the whole building or to a specific part of it. The building partitioning is a process performed according to FprEN 15603 and it allows to associate a building zone to the monitored input data as well as to the actions that a user can perform in a certain zone. Each zone is described with static data such as the technical systems operating in the zone.

The OPTIMUS DSS architecture has been designed as a general framework able to be adapted to any specific public building. According to the architecture diagram shown in Figure 1, the DSS is fed by five domains of dynamic data, each one taken from a different capturing module:

- Weather forecasting: data regarding forecast weather conditions as well as weather data from control units.
- De-centralized sensor-based: data regarding energy and environmental performance, mainly through sensors.
- Social media: data from building occupants through social media regarding comfort aspects.
- Energy prices: data regarding energy prices from the day-ahead market.
- Renewable energy production: data regarding the production of energy from any renewable energy sources.

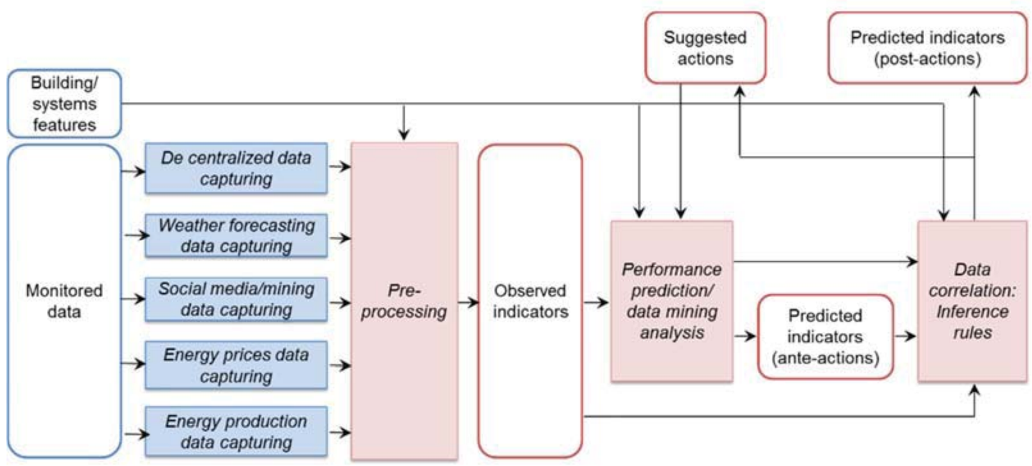

Figure 1 OPTIMUS DSS overall architecture scheme.

Both static and dynamic data are pre-processed (aggregated, statistically elaborated, among others) by a specific DSS module to give as output some observed indicators aimed at describing the building zone behaviour before the actions are applied. The building zone performance prediction is assessed through data driven models. The black box as well as the grey box approach have been adopted. These methods have been preferred to direct simulation models because they allow to evaluate the as-built system performance through measured variables instead of detailed building static data, usually difficult to obtain. The predicted indicators, the observed indicators, and the building and systems features affect the inference rule process. Each inference rule is a string of logical propositions consisting of premises and a conclusion. The premises involve dynamic and static data while the conclusion is a suggested action which is carried out by the users.

3 Semantic Framework

One of the key pillars of a DSS is data provisioning, in particular it is challenging because data are generated by different sources such as physical sensors installed in buildings (e.g., energy consumption), national agencies (e.g., weather forecast, energy prices) and web services (e.g., social media networks). Moreover, data belongs to different realms but they are interconnected and have different characteristics (e.g., units of measure, aggregation level, data encoding).

The Semantic Web concept coined by Tim Berners-Lee is a widely adopted solution to integrated heterogeneous data sources from different realms. This concept has been particularly increasingly applied in governments and cities thanks to the open data and transparency movements (Lopez et al 2012). The Semantic Web community, in particular when referring to the Linked Data movement, promotes the use of ontologies to connect heterogeneous sources of data handled by domain experts.

According to Gruber (1993), an ontology is an explicit specification of a conceptualization where "conceptualization" is a simplified view of the world that is modelled for a particular purpose, thus the knowledge that one might want to model should be explicitly specified by means of concepts and relations formally coded in a particular language such as Ontology Web Language (OWL). Interoperability issues come up when data from different domains and sources is integrated. This situation can be solved through the creation of a global ontology which encapsulates all the domains and particularities of the data sources with the final purpose of having the data integrated according to a shared conceptualization. Based on a global ontology, data is encoded in Resource Description Language (RDF) enabling to describe Web resources under a common and a general-purpose language designed to be read and understood by computers. Semantic information can be formalized in RDF graphs as a set of RDF triples —subject-predicate-object statements—, to represent facts and relations which are represented by an ontology. Through a data link level defined in RDF graphs, it is possible to create a network of linked data available for any application.

To overcome the challenge of data integration in a context of a decision support system in an energy efficiency domain, we have devised a semantic framework which is composed of:

- a shared conceptualization of the urban and building domain including monitoring devices, formally implemented as the OPTIMUS ontology coded in OWL.
- semantic integration process for capturing and modelling data sources from different domains.
- a set of RDF templates used by the data, capturing modules for modelling real-time information items according to the OPTIMUS ontology.
- a publish-and-subscribe system as a communication infrastructure between the data capturing modules and the DSS implemented with the Ztreamy system (Fisteus et al 2014) and a semantic service which processes the data with the purpose of contextualizing them.

3.1 Semantic Data integration process

A data integration process has been devised in the OPTIMUS project to fulfil the following requirements:

- data capturing module communication with the DSS based on a publish-and-subscribe system.
- semantic representation of the data based on existing ontologies, vocabularies and ISO/CEN standards.
- easy deployment and reconfiguration of the different components of the DSS.

The data integration process is based on Semantic Web technologies encompassing four steps: 1) data translation, 2) data communication, 3) data contextualization, and 4) data storage (Figure 2). The data integration process relies on four components: data capturing modules which retrieve the raw data from its source and transform them into RDF, a published-and-subscribe system (i.e., Ztreamy server) which receives data from modules and ensures the connectivity with the DSS, a Semantic Service developed within the project to contextualize the data sent by the modules, and a triple store (i.e., Openlink Virtuoso Server) to integrate the data. The purpose of the data integration process is to be easily replicated with new data and contexts and also be easily scalable to include new data capturing modules or streams. In this way, the process includes RDF templates to generate RDF triples and guidelines for stream naming which will help the future expansion of the approach.

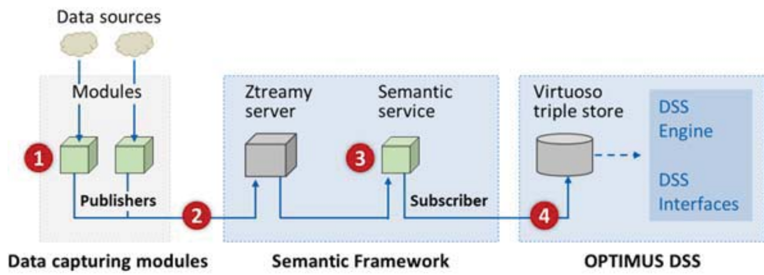

Figure 2 Semantic data integration process.

3.1.1 Step 1: Data translation

The data capturing modules translate the data from the original format into RDF according to a global ontology, namely OPTIMUS ontology. The data is modelled using triples with "subject–predicate–object" expressions which reflect the structure of the OPTIMUS ontology. In order to model the monitored data in RDF, the data capturing modules fill a template by instantiating a set of variables (Figure 3). The idea is that some of the variables can be externally configured (e.g., city name, sensor name) and other variables are generated on-the-fly (e.g., timeid, observation id, value). In this way, it will be easy to deploy the capturing modules in different scenarios. The triples follows the OPTIMUS ontology which is deeply described in section 3.2 of this document.

```
#Global variables
{city}: city_name                                                      (e.g. sant_cugat)
{resource_uri}: www.optimus-smartcity.eu/resources/{pilot}             (e.g www.optimus-
smartcity.eu/resources/{city})
#Variables with regard a particular sensor
{sensor}: sensor_name                                                  (e.g. sunnyportal_solar_radiation)
#Variables with regard a "data point" of a sensor
{timeid}: {year}{month}{day}{hour}{miute}{second}{millisecond}         (e.g. 201409251739000)
{time_in_xsd}: {year}-{month}-{day}T{hour}:{miute}:{second}Z           (e.g. 2014-09-25T05:10:00:00Z)
{value}: numeric value of the monitored data                           (e.g. 23)
{id}: unique ID by event data                                          (e.g. 123456)

<{resource_uri}/observation/{sensor}{id}>    ssn:observedBy              <{resource_uri}/sensingdevice/{sensor}>.
<{resource_uri}/observation/{sensor}{id}>    ssn:observationResult       <{resource_uri}/sensoroutput/{sensor}{id}>.
<{resource_uri}/observation/{sensor}{id}>    ssn:observationResultTime   <{resource_uri}/instant/{timeid}>.
<{resource_uri}/sensoroutput/{sensor}{id}>   ssn:hasValue                "{value}"^^xsd:decimal.
<{resource_uri}/instant/{timeid}>            time:inXSDDateTime          "{time_in_xsd}"^^xsd:dateTime.
```

Figure 3 Variables and the template for generating RDF triples.

3.1.2 Step 2: Data communication

The RDF data is sent to the DSS using Ztreamy, a publish-and-subscribe system whose main purpose is to publish streams of semantically-annotated data with special focus on scalability. Each data capturing module publishes its data through a set of channels/streams, one stream per specific sensor of physical quantity or type of information. A data capturing module can have more than one sensor and a sensor can monitor more physical phenomena. Every monitored data item is sent on a single stream. Streams are identified with a name which should be setup on the server known both to publishers (i.e., data capturing modules) and to subscribers (i.e., DSS).

3.1.3 Step 3: Data contextualization

The Semantic Service receives the RDF triples from the publish-and-subscribe system and processes them. Received data is interpreted in the context representing the information about the sensor characteristics: context is represented by a set of triples which describe the static features of the sensor which is sending data. Figure 4 is an example of the RDF triples needed to contextualize the data such as the property measured by the sensor.

```
<{uri}/observation/sunnyportal_solar_radiation{id}>    ssn:featureOfInterest   <{uri}/featureofinterest/solar_irradiation>.
<{uri}/observation/sunnyportal_solar_radiation{id}>    ssn:observedProperty    <{uri}/property/solar_radiation>.
<{uri}/sensoroutput/sunnyportal_solar_radiation{id}>   rdf:type                optimus:Solar_IrradiationSensorOutput.

<{uri}/sensingdevice/sunnyportal_solar_radiation>      rdf:type                optimus:SunnyPortal_SolarRadiation.
<{uri}/featureofinterest/solar_irradiation>            rdf:type                optimus:Solar_IrradiationFeature.
<{uri}/featureofinterest/solar_irradiation>            ssn:hasProperty         <{uri}/property/solar_radiation>.
```

Figure 4 RDF triples generated by the Semantic service to enhance the RDF data sent by the modules.

3.1.4 Step 4: Data storage

The Semantic Service uploads the final RDF triples in a triple store (i.e., Openlink Virtuoso server). The DSS components, such as the front-end interfaces and the DSS engine, access the triple store by means of the SPARQL Query Language for RDF queries.

3.2 The OPTIMUS ontology

The OPTIMUS ontology is a formal shared conceptualization of the building's operation and the related data, with the purpose of increasing the energy efficiency. It contains the terms and attributes that describe regions, cities, neighbourhoods, buildings, building partitions, systems and metering devices. The OPTIMUS ontology also includes indicators such as energy consumption and CO_2 emissions, as well as climate and socio-economic factors that influence energy consumption. The purpose of defining a global ontology is twofold:

- to reach a consensus about the meaning of terms such as, elements of buildings (e.g., zone, area, sector, floor), units (e.g., Celsius, kWh) and how they interrelate.
- to integrate the diverse data sources using an agreed terminology.

3.2.1 Ontology structure

The ontology models the static (e.g., building and technical systems features) and dynamic (e.g., sensors and metering) characteristics of the buildings including their context such as climate conditions and energy prices. A best practice of the ontology design processes is to reuse existing ontologies or vocabularies for not reinventing the wheel and to increase the interoperability of the resultant ontology. The OPTIMUS ontology is based on two already existing ontologies: Urban Energy ontology[6] and Semantic Sensor Network ontology[7].

For the static part, the Urban Energy ontology has been extended to model the building and to technical system features such as building geometry, building thermal envelope, DHW systems, space cooling/heating systems, and energy generator, among others (Nemirovski et al 2013). The urban Energy ontology is based on international standards. In particular, energy model terminology is specified in ISO/IEC CD 13273 Energy efficiency and renewable energy sources, ISO/DTR 16344 Common terms, definitions and symbols for the overall energy performance rating and certification of buildings, ISO/CD 16346 Assessment of overall energy performance of buildings, ISO/DIS 12655 Presentation of real energy use of buildings, ISO/CD 16343 Methods for expressing energy performance and for energy certification of buildings, and ISO 50001:2011 Energy management systems. The Urban Energy ontology has been selected because it conceptualizes the same domain as the OPTIMUS ontology and it is based on existing energy information standards. Those concepts and properties not found in the Urban Energy ontology have been created under the OPTIMUS ontology.

For the dynamic part, the Semantic Sensor Network (SSN), ontology has been selected. The SSN ontology can describe sensors and observations. In particular, the ontology includes terms of capabilities, measurement processes, observations and deployments in which sensors are used (Compton et al 2012). The ontology is aligned with an upper ontology (i.e., Dolce Ultra Light ontology) and is compatible with SensorML and O&M (Observations and Measurements) standards of the Open Geospatial Consortium. The SSN ontology is based on the Stimulus-Sensor-Observation ontology design pattern. Compton and colleagues describe sensors (i.e., ssn:Sensor) as a physical objects that observe and transform incoming stimuli into another representation, where stimuli (i.e., ssn:Stimulus) are changes or states in an environment that a sensor uses to measure a property, and observations (i.e., ssn:Observation) are contexts for interpreting incoming stimuli and fixing parameters such as time and location. Since the SSN ontology provides only core concepts, it needs to be extended with domain specific terms. These specific terms, already existing in the Urban Energy model, have been used and the ones that are not covered by the Urban Energy model have been created as concepts of the OPTIMUS ontology.

The Figure 5 shows an excerpt of the OPTIMUS ontology to conceptualize the dynamic part, in particular two energy production sensors. In the figure, there is one sensor –SunnyPortal– composed of two subsystems –SP_EnergyProduction and SP_SolarRadiation– that deployed in a generic platform that can be located in different places –building, room, and technical system– modelled with specific terms created for the OPTIMUS ontology. The sensors observe properties (i.e.,

[6] http://www.semanco-tools.eu/urban-enery-ontology
[7] http://www.w3.org/2005/Incubator/ssn/ssnx/ssn

PVSystem_Peak_Power and Solar_Irradiation) defined in the Urban Energy ontology. The outputs of the observations are modelled with OPTIMUS concepts such as PVSystem_Peak_PowerSensorOutput and Solar_IrradiationSensorOutput.

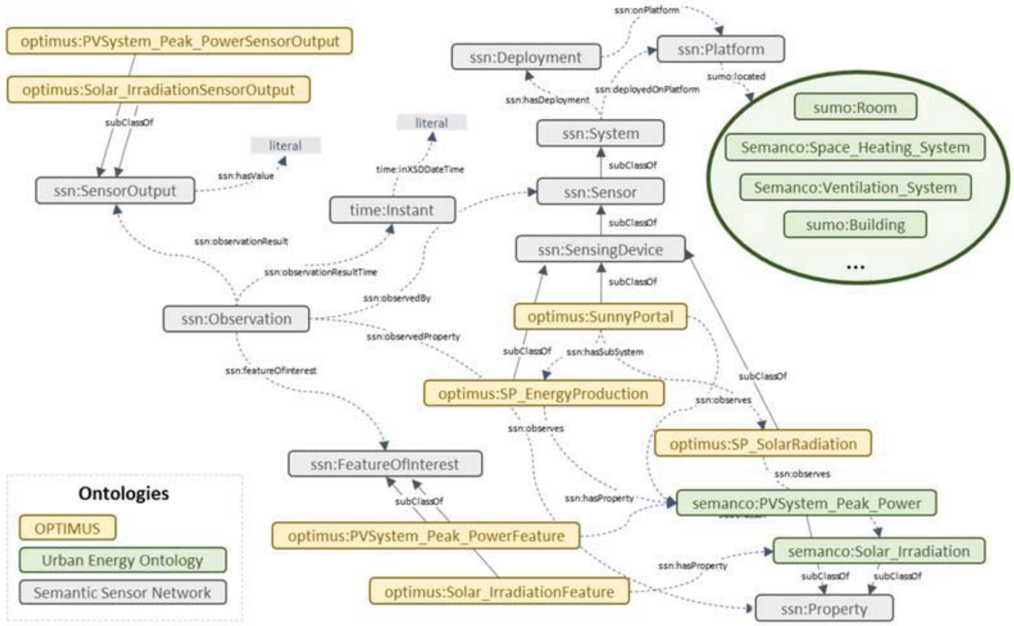

Figure 5 An excerpt of the OPTIMUS ontology.

3.2.2 Ontology coding

The ontology has been coded in OWL language by means of the ClickOn ontology editor developed in the SEMANCO FP7 project (Wolters et al 2013). This editor provides a user-friendly interface which facilitates the process of ontology building. The interface of Click-On editor[8] is composed of two simultaneous views of an ontology: one for editing the taxonomy of concepts (e.g., family of sensors), and another for editing the aggregation relations (e.g., sensor output).

The OPTIMUS ontology, at this time of writing, is composed of 74 terms and 33 relations. Moreover, it can use the 1000 terms and relations of the Urban Energy and Semantic Sensor Network ontologies.

4 Application case: Using integrated data for predicting

The research work presented in this document has been validated in three different scenarios which comprise three buildings located in Sant Cugat (Spain), Savona (Italy) and Zaanstad (The Netherlands).

The semantic data integration process has been applied to gather real-time information from five different sources. The RDF templates have been used in the data capturing modules to transform raw data into RDF according to the OPTIMUS ontology. In the data communication step, 48 streams have been created to obtain data from the buildings and their context such as: energy prices, renewable energy production, solar radiation, outdoor/indoor temperatures and humidity, energy consumption, social media messages, and weather forecast; among others. Data transmitted through the streams are stored in an Openlink Virtuoso server instance with a total –at the time of writing– of 310.752 different entities, 2.298.914 triples, and 75 different classes defined within OPTIMUS ontology.

The OPTIMUS DSS predicts the future behaviour of the building and its context based on real-time data to suggest short-term actions to an energy manager with the final purpose of increasing energy efficiency of the building. A set of prediction models have been developed based on data-driven methods, particularly based on the ones of the grey and black boxes. For example for predicting the energy production of photovoltaic panels, a multiple linear regression (MLR) model has been implemented with a total of 13 regressors which takes into consideration the year, month, hour, solar radiation, humidity, dew point, wind speed, and their combinations. In this case, a MLR model has

[8] http://www.semanco-tools.eu/click-on

been selected due to the linearity of the input variables. Moreover, this kind of models have been applied in similar contexts such as De Giorgi and colleagues did (2014).

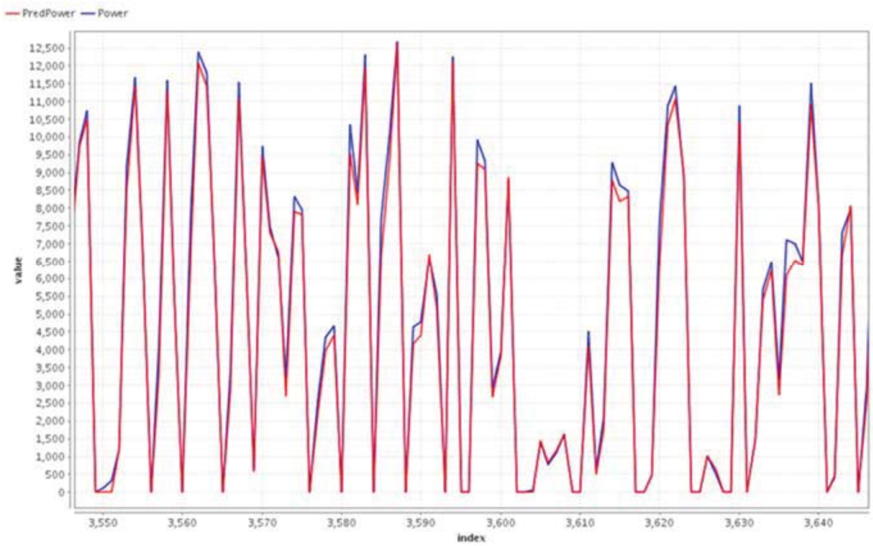

Figure 6 Comparison between the measured energy production –in blue– and the predicted –in red– by OPTIMUS.

Figure 6 shows a comparison between the measured energy production obtained through the semantic framework and the energy production forecast by the OPTIMUS prediction models. The Symmetric Mean Absolute Percentage Error (SMAPE) of the sample was 6.41% with a total of 1 year of measurements, 24 values for each day.

The prediction models have been integrated in the RapidMiner Server environment[9] which enables the publication of the models as Web Services. In this way, the OPTIMUS DSS can asynchronously invoke the models overnight and present the results early in the morning to the energy managers.

5 Conclusions

In the OPTIMUS project we have proposed and implemented an approach to modelling energy information of buildings and their context using Semantic Web technologies. The main benefit of this approach the having the possibility to deal with the heterogeneity of systems, domains, data and applications in an agreed and shared manner.

A semantic framework has been devised to put together real-time data measured by different applications and systems in diverse contexts based on Ztreamy –a publisher-and-subscriber communication system– and on the OPTIMUS ontology which reuses existing ontologies. The framework has been deployed in three different scenarios and a set of prediction models has been developed to forecast the building behaviour.

Next step of the project is to implement the different inference rules which analyse the predicted data with the purpose of suggesting action plans to the city energy manage.

Acknowledgements

Part of the presented work is based on research contacted within the project "OPTIMising the energy USe in cities with smart decision support system (OPTIMUS)", which has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 608703.

References

[9] https://rapidminer.com/products/server/

Arnott, D., & Pervan, G. (2005). A critical analysis of decision support systems research. Journal of information technology, 20(2), 67-87.

Blomqvist, E. (2012). The Use of Semantic Web Technologies for Decision Support - A Survey, In: Semantic Web Journal, 5(3): 177-201, IOS Press.

Calvanese, D., De Giacomo, G., Lenzerini, M., Nardi, D., & Rosati, R. (1998). Description logic framework for information integration. In KR (pp. 2-13).

Baker, C., Shaban-Nejad, A., Su, X., Haarslev, V. and Butler, G. (2006). Semantic web infrastructure for fungal enzyme biotechnologists. Journal of Web Semantics, 4 (3):168–180.

Compton, M., Barnaghi, P., Bermudez, L., GarcíA-Castro, R., Corcho, O., Cox, S., Graybeal, J., & Taylor, K. (2012). The SSN ontology of the W3C semantic sensor network incubator group. Web Semantics: Science, Services and Agents on the World Wide Web, 17, 25-32.

Corry, E., Coakley, D., O'Donnell, J., Pauwels, P. and Keane, M. (2013). The role of Linked Data and the Semantic Web in Building Operation. Proceedings of the 13th annual International Conference for Enhanced Building Operations (ICEBO). Montréal, Canada.

Costa, G. & Madrazo, L. (2014). An information system architecture to create building components catalogues using semantic technologies. Proceedings of the 10th European Conference on Product & Process Modelling. Vienna, Austria, (2014) 551-558.

Ding, C., Wald, M., & Wills, G. (2015). Linked data-driven decision support for accessible travelling.

Fisteus, J. A., García, N. F., Fernández, L. S., & Fuentes-Lorenzo, D. (2014). Ztreamy: A middleware for publishing semantic streams on the Web. Web Semantics: Science, Services and Agents on the World Wide Web, 25, 16-23.

Gruber, T.R. (1993). Toward principles for the design of ontologies Used for Knowledge Sharing. International Workshop on Formal Ontology. Kluwer Academic Publishers.

Keen, P.G.W. & M.S. Scott-Morton. (1978). Decision Support Systems: An Organizational Perspective. Reading, MA: Addison-Wesley.

Lopez, V., Kotoulas, S., Sbodio, M. L., Stephenson, M., Gkoulalas-Divanis, A., & Mac Aonghusa, P. (2012). Queriocity: A linked data platform for urban information management. In The Semantic Web–ISWC 2012 (pp. 148-163). Springer Berlin Heidelberg.

Nemirovski, G., Nolle. A., Sicilia, A., Ballarini, I. and Corrado, V. (2013). Data Integration Driven Ontology Design, Case Study Smart City. In: 3rd International Conference on Web Intelligence, Mining and Semantics (WIMS '13), Madrid.

Pont, U. J., Ghiassi, N., Fenz, S., Heurix, J., & Mahdavi, A. (2015). SEMERGY: Application of semantic web technologies in performance-guided building design optimization.

Power, D. J. (2002). Decision Support Systems: Concepts and Resources for Managers. Westport, CT: Greenwood/Quorum.

Sicilia, A., Madrazo, L. & Pleguezuelos, J. (2014). Integrating multiple data sources, domains and tools in urban energy models using semantic technologies. Proceedings of the 10th European Conference on Product & Process Modelling. Vienna, Austria, (2014) 837–844.

Sprague Jr, R. H. (1980). A framework for the development of decision support systems. *MIS quarterly*, 1-26.

Turban, E., Aronson, J.E., & Liang, T.P. (2005). Decision Support Systems and Intelligent Systems. New Jersey, Pearson Education, Inc.

Wolters, M., Nemirovski, G. & Nolle, A. (2013). ClickOnA: An Editor for DL-Lite$_A$ based Ontology Design. In 26th International Workshop on Description Logics. Ulm, Germany.